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A Neural Network Approach to Modeling the Effects of Barrier Walls on Blast Wave Propagation

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ABSTRACT

A practical means of reducing the impact of blast loads on buildings is to introduce a barrier wall between the explosive device and the building. The height and location of the barrier wall are key design variables in terms of effectively reducing the peak positive and negative overpressure and impulse on the building. Until recently, set-ups that included a barrier between the explosive device and the building could only be modeled with consistent accuracy by using numeric simulation techniques. Unfortunately, these models require many hours of processing time to complete a simulation run, even for the fastest of today's computers. This has led several researchers to consider the use of advanced empirical modeling methods, specifically artificial neural networks, to overcome problems of computationally expensive simulations. Neural networks have the potential to make predictions of the influence of a barrier on blast propagation in a matter of seconds using a desktop computer, thus making it easier for designers to hone-in on an optimal solution. Artificial neural networks appear to be well suited to this application, performing well for problems that are strongly non-linear and comprise many independent variables. This paper reports on past and on-going research in this field at AFRL Tyndall, using both scaled-live experimental data and simulated data to develop the neural models. The design and validation of these models are presented, and their successes and deficiencies are discussed. The paper concludes with an overview of current and future research plans to take this work to a state suitable for use in the field, and to extend it to problems comprising significantly more complicated configurations of structures than a barrier positioned between the explosive device and a building.

INTRODUCTION

This paper is concerned with the development of a method of modeling the propagation of blast waves in a built-up environment that is accurate and can generate results rapidly (in a matter of minutes). Such a tool would allow engineers to optimize the design of new buildings in terms of blast-mitigation performance and cost-effectiveness, including retrofits of existing buildings, and the design of protective structures such as blast walls.

Existing blast modeling tools involve a trade-off between the complexity of the environment they can model and the time they take to generate results. Modeling tools that can produce results rapidly (the empirical models, see for example, Remennikov [1]) are limited in terms of the complexity of the environment they can consider. Often, the problem is simplified to one in which a blast wave propagates over a single blast barrier onto the face of a building, and acts across a vertical line over the face of that building, such as shown in Figure 1. Blast waves propagating through more complex environments, and acting in two or three spatial dimensions, can usually only be modeled using CFD techniques (Computational Fluid Dynamics) (such as ANSYS[2]). Unfortunately, 3-dimensional CFD models, even when limited to a single barrier and building configuration and run on a supercomputer, can take several days or more to complete a single simulation run.

In an attempt to overcome these problems, several researchers have considered using artificial neural networks (ANN's) to model the effects of blast waves on buildings. ANN's are, in essence, an empirical modeling method in that they are usually developed directly from experimental data. They are, however, very versatile, capable of considering many input variables that have a non-linear relationship to the output (dependent) variables [3]. This, in principle, gives them the potential to model more complex bomb-building configurations than considered to date. Remennikov and Rose [4], for example, considered five input variables that embraced all configurations of the problem represented by Figure 1 plus the height of the bomb above the ground (note, the size of the charge, W , was removed from their analysis using inverse cube-root scaling). The outputs considered in their study included peak pressure (kPa) and impulse (kPa-msec) (the integral of the pressure-time envelope), and the network was trained based on data from miniature experiments (Chapman et al., [5]). Similar work has been undertaken by the authors of this paper, as detailed below, which includes as additional parameters the lateral position on the face of the target building, and the time into an event, enabling visualization of the time-wise evolution of the pressure wave over critical surfaces.

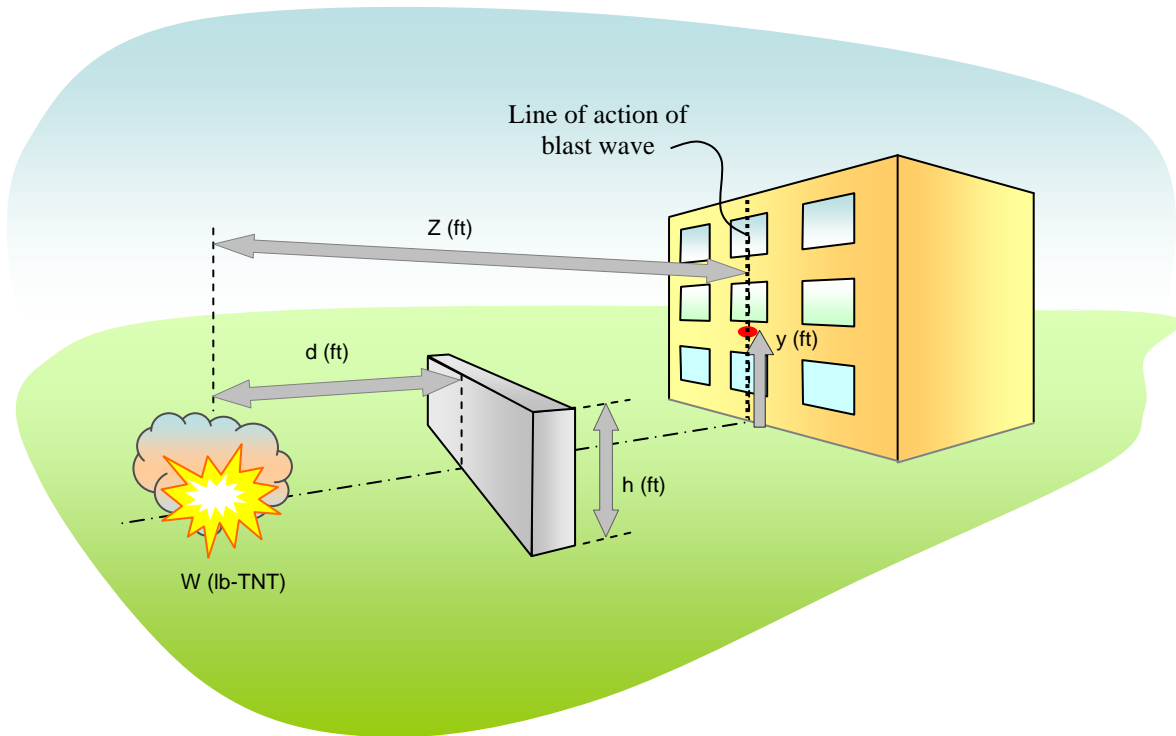


Figure 1: Simple Bomb-Barrier-Building Configuration, with Blast Wave Acting along a Vertical Line on the Target Building

The above studies used the ANN's as simple vector mapping devices, that is, as models that map directly from a set of inputs to a set of outputs. Their scope of application represents about the limit of what can be achieved using ANN's in this way. Extending these studies to include additional input variables would require an increase in the number of experimental data points beyond what is reasonably attainable in a blast modeling environment, where data must either be obtained from live experiments or expensive CFD simulations.

This paper first describes progress using ANN's as vector mapping devices to solve the blast wave modeling problem, illustrating the performance and limits of this approach. It then outlines a proposed radically new ANN-based approach, using the concept of CGM (coarse-grain modeling). Other simulation applications of the CGM approach [6] suggest that it has the potential to simulate rapidly the propagation of blast waves through complicated built environments, comprising many structures arranged within a 3-dimensional space.

PREDICTING PEAK PRESSURE USING ARTIFICIAL NEURAL NETWORKS AS VECTOR MAPPING DEVICES

The first study conducted was a proof of concept that considered the configuration of input parameters shown in Figure 1, where $Z (ft)$ is the distance from bomb to building, $d (ft)$ is the distance from the bomb to the barrier, $h (ft)$ is the height of the barrier, and $y (ft)$ is the height at the building where the effect of the blast is estimated. The charge, $W (lb-TNT)$, was removed from the problem by scaling all distances by $W^{1/3}$, a scaling parameter that has been shown to work well for a broad range of free field experiments (see, for example, Mays & Smith [7]). The output variable considered in this study was the *peak pressure (psi)* measured at the location y on the face of the target building.

Data used for training this ANN was obtained using an existing empirical modeling system, PURWall [8] – the intention was to see if the ANN was capable of reproducing its performance. A total of 1,365 patterns were generated at random for training the ANN and an additional 252 (approximately 16% of the total patterns) were generated at random for testing its accuracy. The values for the inputs for these patterns were generated at

random from within the problem domain, the boundaries of which were constrained by the PURWall software, and are defined in Table I.

Table I: Boundaries of Input Variables for Generating the Training and Testing Patterns

<i>Input Variable</i>	<i>Minimum Value</i>	<i>Maximum Value</i>
Scaled Z (ft·lb-TNT ^{1/3})	4.0	12.0
Scaled d (ft·lb-TNT ^{-1/3})	0.5	3.0
Scaled h (ft·lb-TNT ^{-1/3})	0.8	4.0
Scaled y (ft·lb-TNT ^{-1/3})	0.0	5.0

The RGIN neural network system was adopted for this study since it has been found to perform well for problems where training uses large data sets [9]. Figure 2 shows the progress of training, measured as mean absolute error versus the number of Gauss units that have been trained for the network. Note that in the RGIN system, the network is developed one Gauss unit (hidden neuron) at a time. Each Gauss unit is trained by focusing it in the section of the problem domain where the network is generated the largest errors. The Gauss unit is trained using an error-gradient technique to remove as much of this error as possible. Once a Gauss unit has been trained, the residual errors for the training patterns are recalculated, and are used to determine the focus for the next Gauss unit, and to train it. By this approach, the first Gauss units make the biggest contribution to solving the problem and are the most generalized across the problem domain. Successive Gauss units make less of a contribution to the solution and their spheres of influence are typically more localized within the problem domain.

Figure 2 shows separate progress curves for the training patterns and the testing patterns. Training was allowed to proceed until there was little further improvement in performance measured for the testing patterns, which occurred at around 100 Gauss units. The mean absolute error for the testing patterns at this stage was 0.91 psi, about 3%.

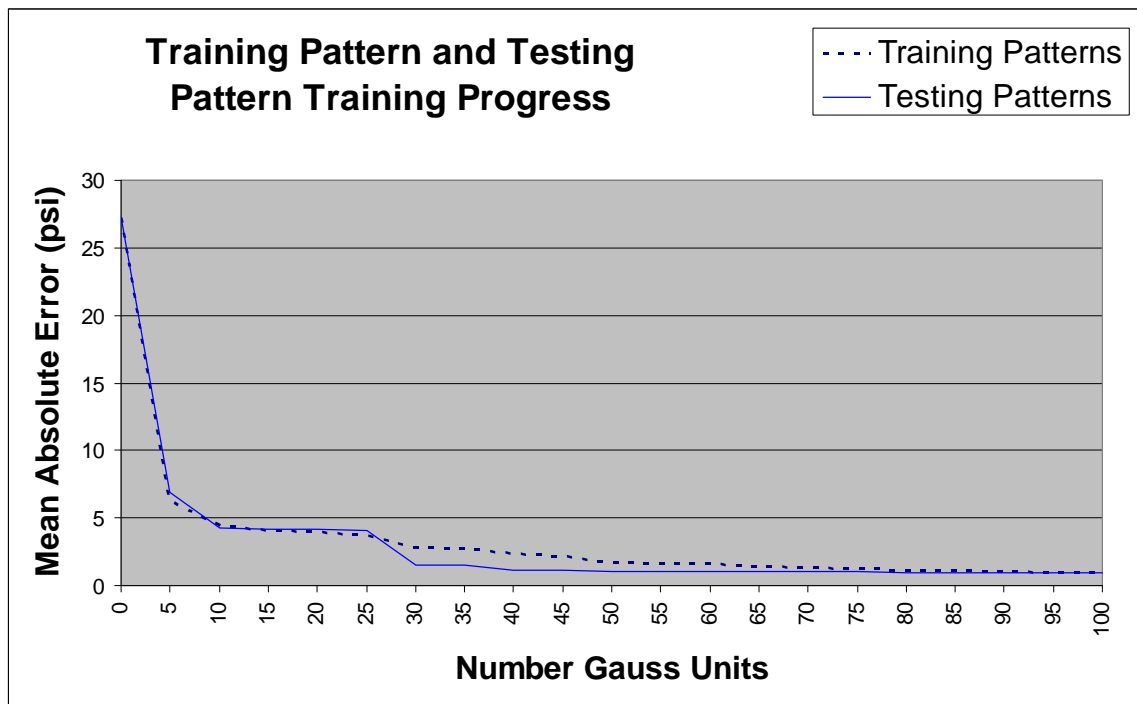


Figure 2: Training Progress for the RGIN-Based Model of Bomb Blast Pressures on Buildings

Figure 3 is a scatter plot of actual versus the ANN predicted peak pressures for the 252 test patterns. If the ANN was a perfect model, all points would fall along the 45 degree line shown in the graph. Inspection of this plot indicates the model is highly accurate, and performs consistently well across the range of peak pressure values. This is confirmed by the correlation between the predicted and actual peak pressures, which had a value of 0.9959. Similar performance results were found by Remennikov and Rose [4] in their ANN study trained using scaled live experiments.

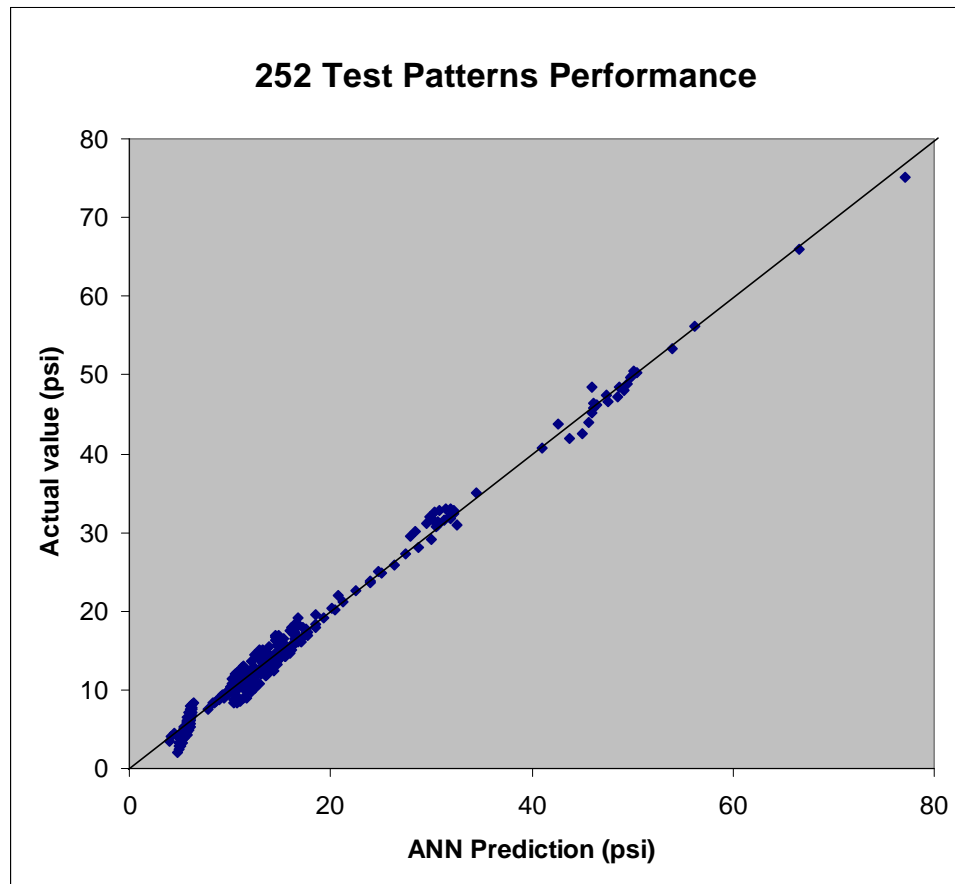


Figure 3: Scatter Plot Validation of the RGIN-Based Model of Bomb Blast Pressures on Buildings

Further analysis showed that the errors for the test patterns were evenly distributed across the problem domain, as illustrated in Figure 4 where errors are plotted against the input variable of height at the building. Plots of the distribution of errors versus all input variables yielded similar results, confirming that the ANN performed consistently well across the entire problem domain.

An attempt to refine this ANN was made by training it so that the first unit would act as a linear function (specifically implementing a hyper-plane since there were 4 input variables) rather than as a Gauss function. The intent was to see if this would allow the ANN to achieve the same degree of accuracy but with fewer Gauss units, based on the idea that a large part of the function could be explained linearly. Figure 5 compares the progress in training for the 252 test patterns, for both the original ANN and the hybrid ANN (containing the linear unit). The graph clearly demonstrates that there is no benefit to including the linear function unit in terms of reducing the size of the network required to achieve the specified level of accuracy.

The results of this study demonstrate the viability of using ANN's to develop a function that maps directly from a vector of input variables (describing a bomb-barrier-building configuration) to the peak pressure at a specified location on the target building. However, while the ANN approach is capable of developing a valid representation of the system used to produce the training patterns, there is still the question of how far this tool can be extended to model more complicated problem configurations. This question is the topic of on-going research at AFRL Tyndall, and is discussed in the following section.

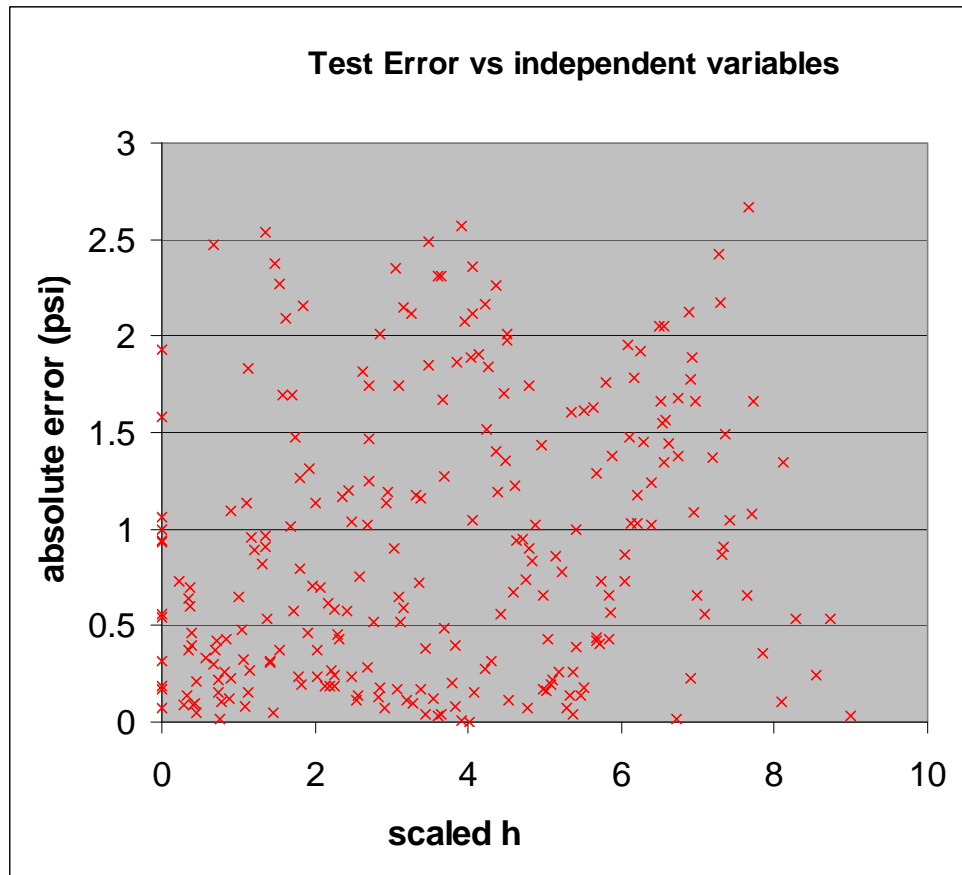


Figure 4: Distribution of Errors for Test Patterns versus Height of Building

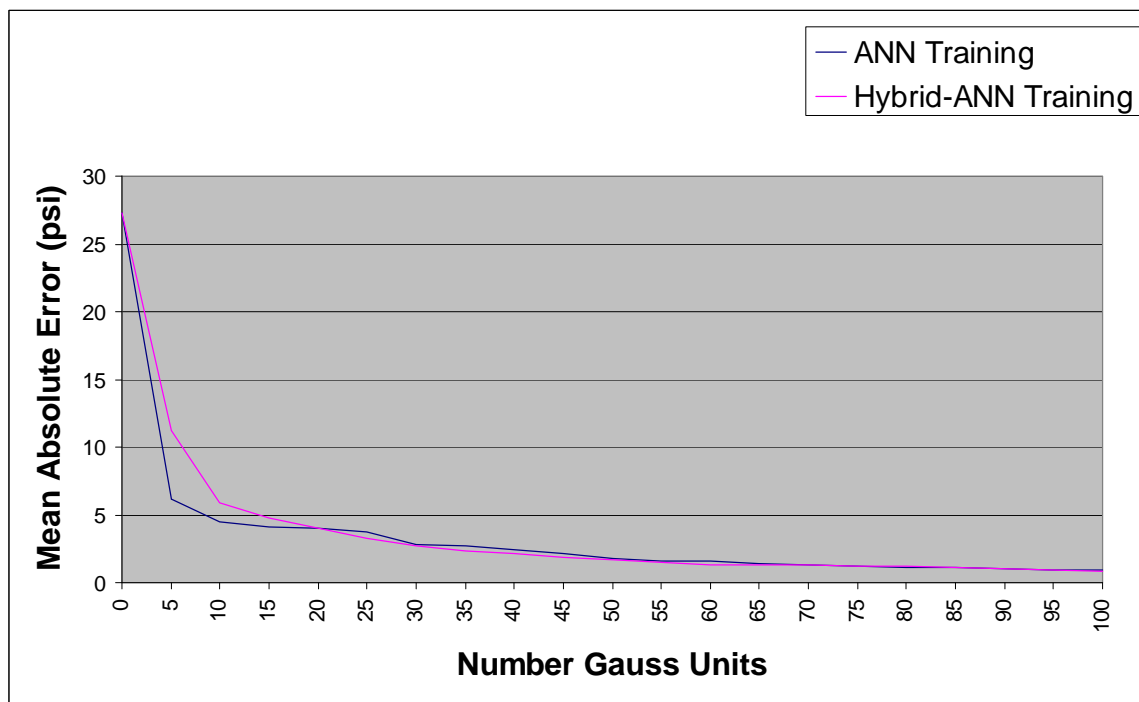


Figure 5: Training Progress for ANN and Hybrid-ANN

ON-GOING AND FUTURE WORK

Current and proposed future work in this area is concerned with maximizing modeling versatility in terms of the range of bomb-building configurations that can be considered. This work is being pursued on two fronts: first, extending the ANN-based vector mapping approach to take into account additional input variables, including time; second, an ANN-based coarse-grain simulation approach that has the potential to model any configuration of structures within the blast field.

PREDICTING THE TIME-WISE EVOLUTION OF PRESSURE USING VECTOR MAPPING ARTIFICIAL NEURAL NETWORKS

A goal of the first of these studies is to predict how pressure changes over time across the surfaces shown in Figure 6, that is, the front and back of the barrier, the front and top of the building, and the ground between the bomb and building. The advantage of this approach is that it will allow the user to view the time-wise progress of the blast wave over these critical surfaces. This, in turn, will allow the engineer to visualize more clearly how a barrier interacts with a blast wave propagating towards a building, and thus make more informed judgments concerning the orientation and design of the barrier.

The output from the ANN models will be estimates of the peaks in the pressure wave, the time to these events, and their decay rate (as indicated in Figure 7) which will allow the pressure-time envelope to be reconstructed and used as the basis of the time dependent simulation of blast-wave propagation.

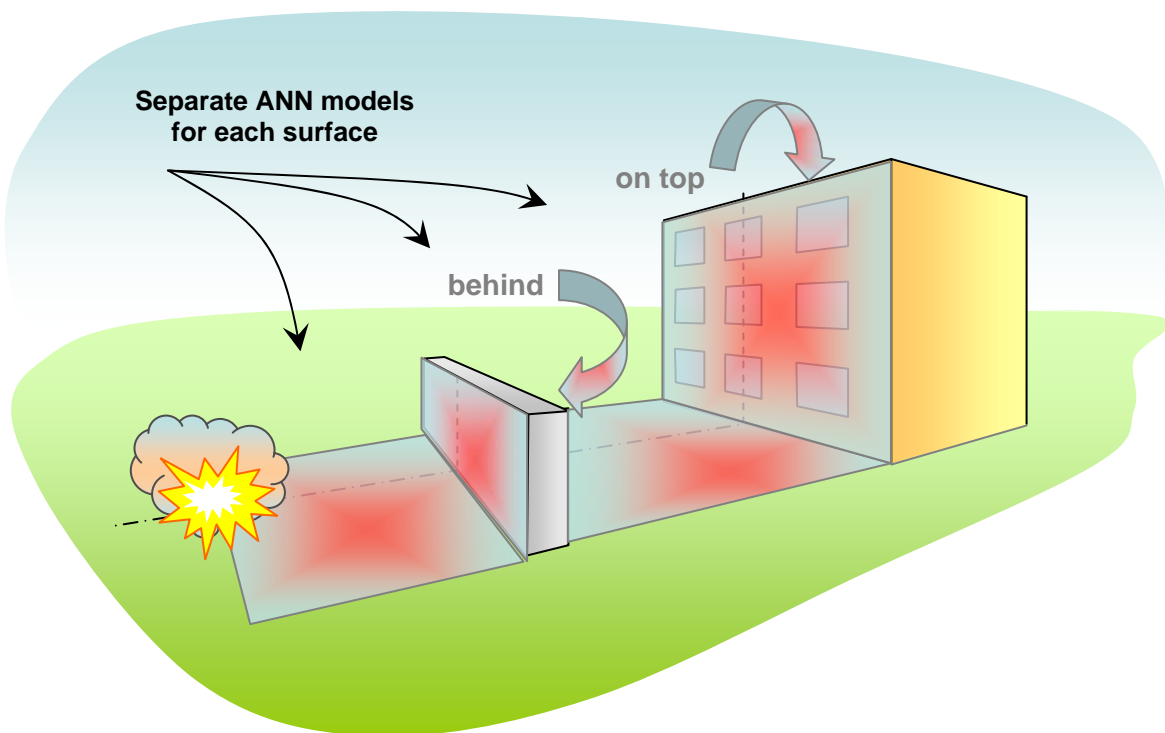


Figure 6: Six Surfaces to be Represented by Separate ANN Models

A second goal of this study is to predict the positive and negative impulses at any location on the relevant surfaces in the problem. These two values are indicated in Figure 8, and are measured as, respectively: the maximum value of the integrated pressure-time envelope; and the difference between the maximum and minimum values of integrated pressure-time envelope.

For this study, the training and testing patterns are being generated using a three-dimensional CFD model [10,11]. The choice of a CFD model was based on the accuracy of this approach, the control provided for the experimental design, and the relative low cost of this approach compared to scaled and full-scale field experiments.

It was decided not to scale distance measures against the inverse cube-root of the charge size in this study due to a lack of evidence that scaling works for situations other than free field setups (that is, setups with no obstacles

in the path of the blast wave, such as barriers). Indeed, preliminary experiments at AFRL Tyndall, comparing CFD simulation results for various scaled representations of the same problem, show inconsistent agreement in pressure predictions, particularly in the proximity of adjoining surfaces. Whether this disagreement is due to errors in the models, or whether it translates to a lack of validity in the scaling assumption, has yet to be determined. Another problem with scaling is that parameters that are fixed in the system used to produce the training and testing patterns (such as barrier thickness in this study) inadvertently become variable with changes in the scale of the end application. This variance is inversely related to scale, so that an increase in the size of the charge would imply a reduction in, for example, the thickness of the barrier. The input variables under consideration in this study are, therefore: W ($lb-TNT$) the bomb charge, Z (ft) the distance from the bomb to the building, d (ft) the distance from the bomb to the barrier, h (ft) the height of the barrier, y (ft) the height on the face of the building where the effect of the blast is estimated, and x (ft) the lateral distance from the centerline on the face of the building.

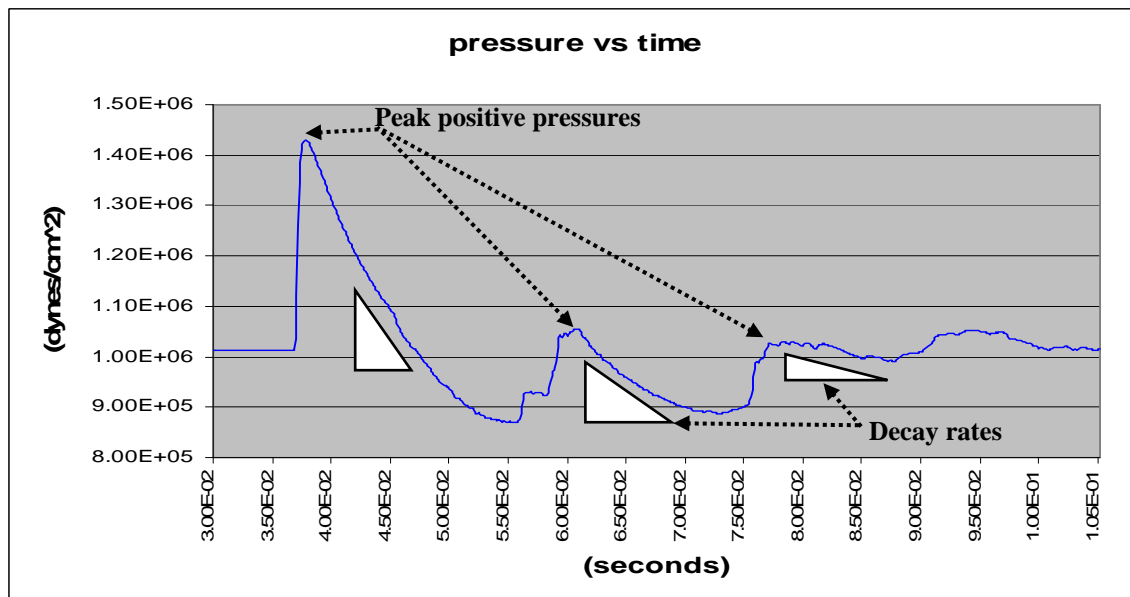


Figure 7: Pressure-Time Envelope Measured at a Specified Location, Showing Peak Pressures

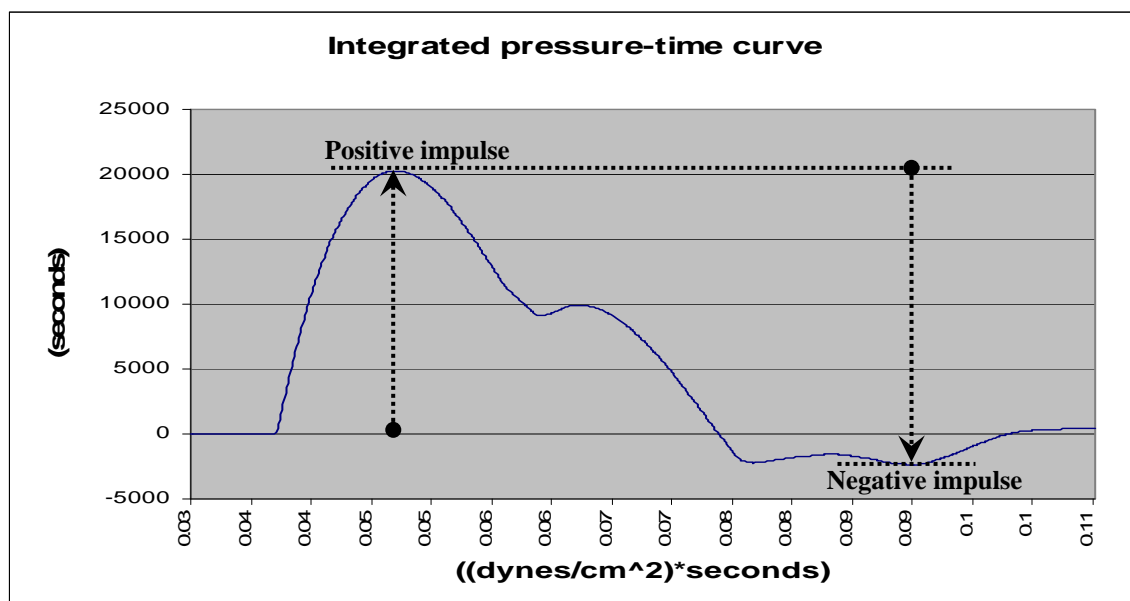


Figure 8: Integrated Pressure-Time Envelope, Showing Positive and Negative Impulses

Modeling Blast Wave Propagation in Complicated Built Environments using an ANN-based Coarse-Grain Method (CGM)

A second on-going study has the goal of developing a simulation modeling system that has the versatility of CFD simulations (namely, an ability to model complex three-dimensional configurations) but with a speed of processing that is orders of magnitude faster. The basis of the approach is the coarse-grain method (CGM) already proven to work for modeling dynamic heat-transfer in buildings [6]. The approach has many similarities to conventional numeric simulation techniques, such as the Finite Difference Method, in that the environment is broken-down into a number of discrete spatial elements, the state of each of which is advanced in discrete time steps. The difference, however, is that the spatial mesh in a CGM model is much coarser than traditional numeric simulations. Numeric simulations of processes such as blast wave propagation typically use a mesh resolution of around 50 (mm³), such that a three-dimensional model of a space 100 (m) x 15 (m) x 15 (m) would require in the order of 180 million spatial elements. In the proposed approach, each element may be 1 (m) or larger in size, requiring just 10,000 elements for the previous example, reducing complexity by a factor of 18,000. Moreover, the approach also allows the size of the time steps to be increased significantly, further reducing the amount of processing to be executed in a simulation run.

For fine-grain simulation models, such as the Finite Difference Method, the propagation of a blast wave through the mesh is computed based on known fundamental physical laws. For a CGM model, however, the large size of each element and time-step render these fundamental laws inapplicable. This problem can be overcome by training an ANN to implement the equations representing behavior at this coarser level based on observations from field experiments or, more conveniently, from CFD simulations. The loss of information that results from using large element sizes (which in turn would lead to a significant drop in modeling accuracy) can be overcome by making the ANN based functions sample the state of the system at multiple stages in the time domain (specifically the recent past) as well as the spatial domain (the state of neighboring elements) [6]. This additional input information comes at no extra cost computationally since it is information that will have been generated at earlier steps in the simulation that is simply being recycled.

Using an ANN to calculate the change in state of a coarse-grain element will be more involved computationally than solving the driving equations on a regular fine-grain model, but this computational overhead should be outweighed by several orders of magnitude by the substantial reduction in complexity of the mesh. In the dynamic heat-flow application of the CGM [6], the increase in processing speed relative to a Finite Element Model was found to be more than 3 orders of magnitude. A simulation that takes 1 day to complete using a conventional CFD model would, by this expectation, be completed in about 1 minute using a CGM implementation.

CONCLUSIONS

Empirical methods of modeling the effects of bomb blast waves on buildings are fast and often accurate, but lack the flexibility to model anything other than the simplest of built environments. Artificial neural networks offer a means of extending the scope of application of empirically derived modeling, but still they do not realize the flexibility of CFD simulation. The paper proposes, therefore, a new method of modeling based on simulating within a coarse mesh, made possible by the use of ANNs. The approach has the potential to increase processing speed by several orders of magnitude whilst retaining the versatility of conventional simulation techniques.

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